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Integrating AI with IoT in Operations Management

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Abstract: *Operational management's use of AI signifies a dramatic transformation in company, altering decision-making processes, efficiency, and competitive dynamics across industries. AI reduces errors and increases productivity by automating manual tasks. Examples of this include supply chain optimization algorithms and AI chatbots for customer support. This study compares various machine learning (ML) strategies for supply chain demand prediction, one of the most popular artificial intelligences (AI) approaches. In the current study, support vector machines (SVMs) and artificial neural networks (ANNs) are used in conjunction with more conventional time series prediction methods, such as exponential smoothing and moving average, to predict the supply chain long-term demand. The largest Indian automaker's component supplier's data set is then used to implement this research. The comparison reveals that the forecasts generated by ML algorithms are substantially more accurate and closer to the real data than those generated by conventional methods for predicting.*

Keywords: Operation management, AI, ML, prediction, supply chain, demand

I. INTRODUCTION

In commercial circles, the phrase "artificial intelligence" (AI) is becoming often employed. It's a technique that works with machine intelligence, particularly in computer systems. AI is a vast field of science that straddles the boundaries of arts and sciences, computer science, mathematical information, statistics, operations management and philosophy. The goal of artificial intelligence (AI) is to create nonbiological systems—like computers and machines—that are capable of carrying out tasks that normally call for human intelligence. On the other hand, ML is a branch of AI that concentrates on statistical learning methods.

Operational management's use of AI signifies a dramatic transformation in company, altering decision-making processes, efficiency, and competitive dynamics across industries. Algorithms for supply chain optimisation and AI chatbots for customer service are examples of how AI automates manual tasks, increasing efficiency but also potentially increasing error rates. In addition to improving data-driven insights, this automation frees up resources for strategic endeavours. Artificial intelligence's capacity to examine vast volumes of data leads to a deep understanding of consumer behaviour, market dynamics, and internal operational patterns, which improves strategic decision making. Thanks to AI's predictive analysis, businesses can quickly adjust to changes in the market by foreseeing and mitigating future issues (Kamble et al., 2018).

The ideal approach to solving this large data-related challenge is to use AI approaches also referred to approaches that employ large datasets to automatically identify and extract trends across parameters are known as ML approaches (Biggio & Roli 2018). Machine learning algorithms are capable of producing new insights, pointing researchers in the correct path, and uncovering patterns in data that had not been noticed before. The use of ML techniques can be advantageous for a number of industries, particularly operations, manufacturing, healthcare, and housing (Mansouri et al., 2021).

Moreover, machine learning is widely employed in the administration of many supply chain aspects and domains. Recently, there has been an increase in research interest in ML methods and their potential applications in supply chain management. Owing to the limitations of traditional methods for analysing large volumes of data, scientists are now using ML strategies, which are extremely effective in analysing and interpreting large amounts of data.

The goal of the research is to predict a time-series including pattern and periodic tendencies for an Indian auto parts supplier. ML techniques like SVM and ANN are contrasted with the Mean Absolute Percentage Error(MAPE) index and more conventional time-series prediction methods like moving averages and exponential smoothing with and without patterns. The capacity of these techniques to simulate trends and seasonal variations found in suppliers' data led to their selection.

Objective of Study

- To demonstrate the use of ANNs and SVMs in wholesaler sales prediction.
- To illustrate the differences in the accuracy of wholesaler sales forecasts between different time-series prediction techniques.

II. LITERATURE REVIEW

Management of operations (OM)

Three modules make up operation management (OM): "in the door," "out of door," and any management actions that don't fall into one of these three categories. "In the doors," the initial module, handles the administrative tasks necessary to obtain the necessary inputs. The primary responsibilities in this module are sourcing, purchasing, logistics, and supplier selection. "Out of door," the second module, handles the administrative tasks necessary to deliver products and services to clients. The distributor, retailer, and consumer are the three entities that are the focus of this module (Santiváñez and Melachrinoudis 2020).

According to Morikawa (2017), businesses in both the manufacturing and non-manufacturing sectors anticipate positive effects from AI. As a result, proposition 1a of this study looked into the possible use of AI systems for Proposition 1b's quality function deployment and product inspection. All procedures, including inventory control, logistics, reverse logistics, and outsourcing, are included in the supply chain (Subramanian and Ramanathan 2012; Quiroz and Wamba 2019). Downstream and upstream supply chains are the two segments that make up a supply chain. In the upstream supply chain, selecting a supplier is a frequent decision-making process (Kar, 2015).

IoT in Operations Management

The Internet of Things (IoT) plays a crucial role in amplifying the impact of Artificial Intelligence (AI) on Operations Management by providing real-time, high-quality data essential for intelligent decision-making. IoT-enabled devices, sensors, and smart machines continuously collect operational data, which AI systems analyze to optimize processes, predict outcomes, and automate operational activities.

In operations planning and control, IoT facilitates real-time visibility across production systems, enabling AI-driven demand forecasting, capacity planning, and scheduling. Smart sensors embedded in machinery support predictive maintenance, allowing AI models to detect anomalies, forecast equipment failures, and reduce unplanned downtime, thereby improving asset utilization and operational reliability.

Within supply chain and inventory management, IoT enhances traceability and transparency by tracking materials, products, and logistics in real time. AI algorithms leverage IoT data to optimize inventory levels, reduce lead times, improve supplier coordination, and respond dynamically to demand fluctuations.

IoT also strengthens quality management by monitoring process parameters and product conditions continuously. AI-powered analytics use IoT data to identify defects, detect deviations, and recommend corrective actions, resulting in improved product quality and reduced waste.

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Artificial Intelligence

Artificial Intelligence (AI) is the capacity of a computer to precisely learn from outside inputs and use that knowledge to carry out specific tasks and goals (Haenlein and Kaplan 2019). The learning methods that the framework can employ are semi-supervised, supervised, or unguided (Kar 2016). As per Kumar et al. (2019), artificial intelligence (AI) is a technology that provides an abundance of information and possibilities that may be sorted down to personalised targeting.

Because AI can automate monotonous tasks like scheduling, data entry, and order processing, resources may be allocated to more proactive and value-adding projects. In addition to improving operational efficiency, this shift creates an inventive and adaptable organisational culture—both crucial for being competitive in the fast-paced manufacturing sector (Kinkel et al., 2022).

The evaluation of AI to supply chain operations represents a substantial advancement in the management and optimisation of supply chains by businesses. AI is particularly useful for supply chain optimisation, as it increases accuracy and efficiency in key areas. One such field is demand forecasting, where artificial intelligence algorithms can analyse enormous volumes of data to better correctly estimate future product demand and assist businesses in avoiding excess production or overstocks (Helo and Hao 2022).

III. METHODOLOGY

Forecasting a time-series with pattern and seasonal shifts for an Indian auto parts supplier is the aim of this project. For long-term demand predicted, we employ two ML methods: are SVM and ANN. We predict the same data using conventional time series prediction techniques, such as moving average and exponential smoothing, as a benchmark for comparing ML algorithms.

Supper Vector Machine (SVM)

Unlike neural networks and linear regression, SVMs, a more recent family of universal function correlates, are not predicated on the idea of empirical risk reduction. They are depending on the structural risk reduction concept of statistical learning theory. Structural risk reduction attempts to minimise the true error on an unseen, chose at random test instances, whereas MLR and NN minimise the error for the scenarios that are currently visible.SVM use a higher-dimensional projection of the data to maximise interclass margins and minimise regression error margins. Because the margins are soft, it is possible to find a solution even in cases when the training set contains contradicting samples. The Radial Basis Function (RBF) kernel is one of the kernels that can be utilised to enable higher dimensional space from mapping of non-linear and adjusting the number of errors in relation to the model complexity using a complexity parameter. The method translates into the minimising of the subsequent function:

$$F(f) = \frac{P}{N}\sum_{j=1}^{N}\left|Z_j - f(x_j)\right|_j + \frac{1}{2}|f|^2 \qquad (1)$$

The fact that this function prevents over-fitting by assigning zero loss to mistakes smaller than e is a crucial point. Put another way, this function tube fits with a data radius rather than a precise value. This is comparable to a fuzzy function description. This loss function's second noteworthy feature is that it minimises a least modulus rather than least squares. As we'll see later, the e option also has a significant impact by giving the data a sparse form. Under very broad circumstances, the objective functions minimize can be expressed as follows:

$$F(x) = \sum_{j=1}^{N} p_j Q(x, x_j) \qquad (2)$$

Where is the quadratic problem's solution, denoted by p_j. The referred to as kernel function, (x,xj), is the same as the X. This often-utilised instrument facilitates nonlinear mapping and yields the generalised inner product.A variety of options, including Gaussian, sigmoid, polynomial, and splines, are available for the kernel function.

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Artificial neural Network (ANN)

ANN is a type of generalised nonlinear nonparametric algorithms that are motivated by studies on the nervous system and brain. The majority of predicting systems are drawn to ANNs due to their proven ability to be universal approaches. Furthermore, for modelling unknown functions, ANNs are less expensive than linear subspace techniques like polynomial and trigonometric series. It is widely recognised that a feed-forward network may arbitrarily well imitate any constant functioning, with the output module's transfer function being easily recognised and the middle-layer cells' logistic activities given an adequate number of middle-layer units. As a result, this study employed a three-layer feed forward network.

The parameters that in the multivariate regression framework represent the regressors are connected to the output that represents the regress by using a middle layer.The network model can be expressed as follows:

$$R_t = f(X_t, \beta, \gamma) + \varepsilon_t \qquad (3)$$

Moving average

This technique forecasts the upcoming period using the average of n prior periods. Finding the ideal value for n is the issue.

Exponential smoothing

To mitigate transient fluctuations in the data, these algorithms employ a weighted average of past values. The weight decreases rapidly over time. The forecasting formula is as follows:

$$F_{t+1} = F_t + \beta(B_t - F_t) \qquad (4)$$

Where:

F_t = Forecasted demand at time t+1

B_t = Real demand at time t;

Empirical Results

Here, SVM's suitable kernel function that can forecast with the least amount of error is found. To this end, four different kernel functions are studied: polynomial, sigmoid, RBF, and linear. The MAPE index is used to express the inaccuracies in these forecasts.

The findings displayed in Table 1 indicate that the linear kernel function type is the best choice for this type of data. Figure 1 displays the results of various functions of kernel together with the time it took to solve them.

Table 1: Various kernel functions' output

Kernel Functions	MAPE Value
RBF	173.937
Linear	173.392
Polynomial	188.384
Sigmoid	193.762

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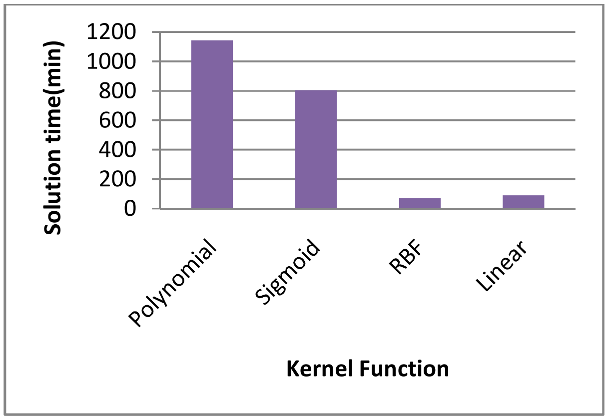

Figure 1: Kernel functions solution time

We can utilise Bayesian regularisation in the training procedure to find out how many parameters the network is using efficiently, irrespective of the overall network parameters number. However, after experimenting with a number of different middle-layer unit and layer counts, we discovered that the lastquantity of units of middle-layer and layers are set to three and three, respectively.

Table 2 displays the outputs of each case's ANN MAPE index.

Number of units in all layers	MAPE	
	3- layer	4- layer
2	167.54	172.19
3	164.71	169.76
4	165.29	165.29
5	167.92	170.58
6	166.47	170.58

We initially examined a values range for n and then MAPE index were computed to determine the ideal value of n. As a result, we determined that 200 was the ideal value for n, and MAPE = 169.842. Table 3 displays the outcome of utilising a moving average.

Table 3: Outcome of applying the moving average method

N	MAPE
2	180.357
4	178.871
10	173.896
30	171.957
60	169.956
80	170.186
100	168.843
150	169.989
200	169.842
300	172.021
500	173.438
1000	174.134

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The demand was projected using exponential smoothing on the data set, and it was discovered that the ideal value for n is 0.01 0. Using this number, the forecasting error was calculated, and the best combination's MAPE index was found to be 1 67.797(Table 4).

Table 4: Outcome of applying the exponential smoothing approach

B	MAPE
.001	169.961
.005	169.963
.010	170.156
.050	169.685
0.100	172.216
0.150	174.632
0.300	175.549
0.450	175.978
0.600	176.531
0.750	176.864
0.900	178.461

The suggested approaches are evaluated for stability using raw data, and the score of MAPE is recalculated for the outcomes. Table 5 displays the least amount of MAPE that was produced by each procedure. The research's suggested artificial neural network (ANN) can be used to estimate demand in a supply chain more effectively than earlier traditional approaches, according to the findings.

Table 5: Using the MAPE index for comparison and model validity

Techniques of prediction	Training Data	Testing Data
ANN	172.253	165.425
SVM	180.735	169.642
Moving Average	182.632	169.686
Exponential Smoothing	183.874	173.174

IV. CONCLUSION

In summary, artificial intelligence (AI) has had a profound and transformative effect on business operations across a wide range of industries. Businesses have been able to improve customer experience, optimise operations, and make data-driven decisions that have improved their overall performance and competitiveness thanks to AI technologies and applications.

To forecast demand in the supply chain one of the operation management parts, this research employs a few ML techniques, which are a subset of AI, including ANN and SVM. The procedure consisted of two steps. The first step involved training an ANN with three layers and three middle units employing sensitivity analysis. Four distinct functions of kernel were then used to determine the optimal function of kernel and parameter arrangement for the SVM technique. Two conventional forecasting techniques were then employed to make the forecast and evaluate predicting errors for all methods using the MAPE index.The outcomes demonstrated that artificial neural networks are more accurate forecasters than previous techniques. The optimal set of parameters from each method is used in the next step for simulation validity and evaluation. The effectiveness of the suggested models is assessed using raw data in the second step. The outcomes demonstrated once more how accurately artificial neural networks can forecast when compared to SVM and other conventional forecasting techniques.

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